

EARTH SCIENCES

Understanding human influence on climate change in China

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ABSTRACT

China's climate has been warming since the 1950s, with surface air temperature increasing at a rate higher than the global average. Changes in climate have exerted substantial impacts on water resources, agriculture, ecosystems and human health. Attributing past changes to causes provides a scientific foundation for national and international climate policies. Here, we review recent progress in attributing the observed climate changes over past decades in China. Anthropogenic forcings, dominated by greenhouse gas emissions, are the main drivers for observed increases in mean and extreme temperatures. Evidence of the effect of anthropogenic forcings on precipitation is emerging. Human influence has increased the probability of extreme heat events, and has likely changed the occurrence probabilities for some heavy precipitation events. The way a specific attribution question is posed and the conditions under which the question is addressed present persistent challenges for appropriately communicating attribution results to non-specialists.

Keywords: human influence, detection and attribution, climate change, climate extremes

INTRODUCTION

Human activity, dominated by the emission of greenhouse gases, has resulted in an increase of about 1.0°C in the average Earth surface air temperature since pre-industrial times [1]. The warming has affected all parts of the climate system, including the atmosphere, ocean, land, cryosphere and biosphere. On a regional scale, surface air temperature over China has warmed at a rate much higher than the global average (Fig. 1) [2]. As the warming continues, its impacts on human and natural systems increase; and global warming becomes the most challenging problem for the world. Central to climate change policy is an understanding of the causes of past climate change, at both global and regional scales.

Since the late 1980s, the successive assessments of the Intergovernmental Panel on Climate Change (IPCC) have established that human influence has resulted in global warming, mainly through the emission of greenhouse gases. When each assessment report was released, it prompted a new set of international climate treaties and/or policies. The

first IPCC report, published in 1990, identified that human use of fossil fuels had substantially increased the concentration of atmospheric greenhouse gases, leading to an enhanced warming effect and resulting in a warming of the Earth's surface [3]. This report brought climate change to the attention of international politics for the first time, serving as the basis for the founding of the United Nations Framework Convention on Climate Change (UNFCCC) in 1992. The release of the second IPCC assessment report in 1996 [4] confirmed that global warming was 'unlikely to be entirely caused by nature' and that human activities have had a 'discernable' impact on the global climate system, resulting in the adoption of the 'Kyoto Protocol'. The third IPCC assessment report [5], published in 2001, provided a scientific consensus that 'most of the warming observed over the last 50 years is attributable to human activities'. This led to the inclusion of both adaptation and mitigation in the UNFCCC negotiations. The fourth IPCC assessment report, released in 2007, concluded that the 'warming of the climate system is unequivocal' and that most of the warming observed

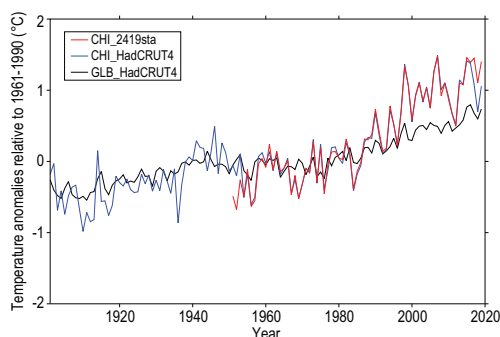


Figure 1. China's surface air temperature has increased at a greater rate than the global mean surface temperature. Clear trends can be seen in the time series for the global (black) and regional (over China) mean (blue) surface temperature in the HadCRUT4 datasets for the period 1901–2018, and also in the regional average (red) calculated from homogenized data at 2419 Chinese observing stations for 1951–2018. Temperature is expressed as the anomaly ($^{\circ}\text{C}$) relative to respective 1961–1990 averages.

since the mid-20th century 'is very likely due to the observed increase in anthropogenic greenhouse gas concentrations' [6]. The conclusions of this report were the scientific basis for the UNFCCC's 'Bali Road Map'. The fifth IPCC Assessment was completed in 2014, stating that 'human influence on the climate system is clear' [7], providing the science foundation for the 'Paris Agreement'. This Paris Agreement aims at holding the increase in the global average temperature to well below 2°C above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5°C above pre-industrial levels. Our understanding of the causes of climate change along with the confidence in this understanding was key in each of these assessments and the international climate policies that they informed.

While international climate policies have significant implications for national policy, understanding regional climate changes is also highly relevant for national climate policymaking as policymakers can relate more directly to climate change at national and regional scales. For this reason, there has been a concerted effort to systematically assess climate change in China since the late 1990s. This effort has resulted in the production of three national climate change assessments [8] and three national science assessment reports on climate and environment changes [9]. Literature on attributing the observed changes in the climate in China to specific causes available to these assessments is limited because research in this field began relatively late in China. However, significant advances have been made in recent years, thanks to the increasing interest of Chinese climate scientists in this subject, and the increasing levels of support from various funding agencies. We

review these recent advances here, focusing on the human influences on China's climate including detection and attribution of long-term changes, and the attribution of changes in the frequency and/or magnitude of high impact climate events. Our review is built on earlier general review papers [10–13], focusing on China to inform ongoing and future national assessments. We also cover new development since those earlier reviews. The paper is organized as follows: we first describe climate change detection and attribution methods to provide a general context for the interpretation of attribution results; we then review the attribution for long-term changes in various variables and recent developments in the field of event attribution; finally, we provide conclusions and suggested directions for future research.

METHODS OF ATTRIBUTION

'Attribution' implies determining the relative importance of different drivers behind a change. The drivers can be both internal to the climate system or external forcing. Internal factors include decadal and multi-decadal natural climate variability. External forcings can be anthropogenic such as greenhouse gas and aerosol emissions or land-use change [6,7], or natural such as volcanic activity. An attribution usually involves collection and quality control of observation data, identification of possible drivers and causality inferencing. There are two types of attribution studies in the climate literature. One deals with the attribution of long-term changes in the mean climate and in climate extremes; the other focuses on the changes in the magnitude or frequency of specific extreme weather and climate events. Methods for both types of study have evolved but the length constraint of this paper prohibits a detailed and comprehensive review of the methodologies. Here, we aim at providing a conceptual framework for methods that are popular in the recent literature and highlighting issues that are relevant to the proper interpretation of the attribution studies.

Long-term climate changes

The objective of most detection and attribution studies for long-term changes in the climate is to determine whether changes have occurred, and if so, to attribute them to specific causes. Regression-based methods, also known as fingerprinting methods, have been widely used. Most of the detections and attribution studies reviewed in this paper use the optimal fingerprinting method [14–17]; for this reason, we will provide a conceptual introduction

and discuss its limitations here. This method regresses observations onto an expected climate response simulated by climate models under different external forcings. The method can be traced back to Hasselmann [18], who coined the term ‘optimal fingerprints’. The link between ‘optimal fingerprints’ and linear regression was made explicit by Allen and Tett [19]. In a nutshell, this method assumes that climate models can correctly simulate the patterns of the climate response to external forcings, even though the magnitudes of the response patterns may differ from the observations. With this assumption, it is possible to regress observations onto model-simulated responses, and detection and attribution analysis is reduced to statistical inferencing about the regression coefficients or scaling factors. The analysis requires three main ingredients: (a) observation data with sufficient spatial and temporal coverage and high quality; (b) climate-model-simulated responses to one or more external forcings, typically estimated as the ensemble averages from multi-model simulations; and (c) estimates of internal variability of the climate which are required for solving the regression problem, and for estimating the uncertainty in the scaling factors and thus making statistical inferences. Internal variability is typically estimated from a large number of pre-industrial climate simulations. Detection of the climate response to a particular external forcing can be claimed if the corresponding scaling factor is significantly above zero, and attribution can be claimed if the confidence interval also includes one and if influences from other external forcings can be excluded.

Regression models with various levels of complexity have been used, depending on how uncertainty is treated for the observations, and the responses simulated by the models. The simplest form of regression, termed ordinary least squares [19], does not consider uncertainty in the observation or in the model-simulated responses. The uncertainty in the estimated responses because of internal variability tends to bias the best estimates for the scaling factors towards smaller values, and underestimates the uncertainty associated with the scaling factors. Consequently, most detection and attribution analyses use the total least squares method (TLS, [14]), which is a more complex model that explicitly accounts for the uncertainty in the estimated responses. Although climate modelling centers have produced large volumes of pre-industrial climate simulations, the availability of these control-run data is still too small for robust estimation of the covariance if the detection and attribution analysis is implemented at high spatial and/or temporal resolution. Additionally, when the amount of simulation data is too small, the covariance matrix may

not be full rank, and may therefore not be invertible. Dimension reduction and the use of regularized covariance [15] have been used to circumvent this problem. While methods exist that consider multiple sources of uncertainty for estimated model responses, imperfect measurement of the observations and internal variability [20–22] mean that their applications have been limited.

Generalized multivariate regression assumes that the regression residuals follow a multivariate Gaussian distribution. This assumption is often justified for means of climate variables. Direct implementation of the optimal fingerprinting method for climate extremes may be problematic because extreme values, such as the annual maximum daily precipitation at a location, would be skewed, and would generally follow extreme value distributions. Two approaches have been used to take into account the distributional property of extreme values, or of indices for climate extremes, in detection and attribution analyses for long-term changes in climate extremes. One approach is to convert the extreme values, such that the new quantities are not skewed, and the distributional assumption of optimal fingerprinting method is satisfied. Two methods have been used for this. One method converts the original observation data into a probability-based index [23–28]. This probability transfer makes it possible to use the optimal fingerprinting method, and makes it easier to compare extreme values at different locations, but the results can be difficult to interpret physically. The second method averages the extreme values over a large region, so that the averages asymptotically approach a Gaussian distribution [29]. A caveat to this method is that it is not always meaningful to average extreme values, for example, extreme precipitation over a large region that encompasses diverse climate conditions and within which observations are unevenly distributed. An alternative approach is to explicitly fit the observations to extreme value distributions that are constructed from the model-simulated responses, as covariates of the distribution parameters [30–32]. A potential problem with this method is that it is difficult to account for the uncertainty in a single estimate.

Specific regional conditions complicate the attribution of regional-scale climate change. For example, urbanization or other land-use changes can enhance or counteract greenhouse gas effects, and local aerosol forcings can play a significant role on the regional scale. Yet these forcings are often not considered in climate simulations, or are poorly represented, making it difficult, and sometimes impossible, to estimate the pattern of the climate response to the applied external forcing. Climate variability is also greater at smaller spatial scales, making it

more difficult to identify regional climate change than global climate change.

Extreme events

Most damage from natural disasters is related to extreme weather and climate. With increased awareness of global warming and an increase in loss and damage, the media and the public often ask whether the human influence on the climate system has caused specific high-impact weather and climate events, such as the 2003 European heatwave and the 2013 hot summer in eastern China during or after the event. New methods have been developed to address such questions, albeit often indirectly. Since the pioneering work of Stott *et al.* [33], event attribution has emerged as a distinct field of science [12,34,35]. It is now possible to estimate the human contribution to changes in the probability for the occurrence of, or magnitude of, such events.

Very few studies attribute a particular event [36], and few studies attempt to conduct ‘end-to-end’ attribution, which is attribution for the impacts of an extreme event [37]. Some recent developments in event attributions rely on process understanding, following what is called ‘a story-line approach’ [38]. However, most event attribution studies focus on a specific class of events and ask whether human influence has affected the probability and/or magnitude of events in that class. For example, while the 2013 summer heatwaves in eastern China may have motivated an event attribution study, the question that is often asked relates to events that are similar, in other words, to the class of events that are similar to the 2013 summer heatwaves. These studies almost always involve a comparison between the magnitudes or probabilities for the event in the factual world (the world that has been), and in the counterfactual world (the world that might have been, had we not emitted greenhouse gases since pre-industrial times). Approaches to these comparisons differ depending on how the factual and counterfactual worlds are constructed, and how the questions are asked [12]. For example, probabilities for an event occurring in both worlds are often estimated to construct the so-called fractional attributable risk (FAR), or risk ratio (RR), which then determines the level of human influence on the event. Estimates of FAR or RR can be quite different if the problem is framed differently, for example, if different metrics are used to describe a particular variable, and/or for the definition, magnitude and rarity of an extreme event, and/or for its spatial and temporal extent [39]. The observation data and climate models, and the method used to estimate the probability, all affect the attribution results.

The conditioning used to simulate the factual and counterfactual worlds is important. When coupled-climate-model simulations are used in event attribution analysis, the only required condition is the external forcing. It is therefore possible to estimate changes that are the result of specific external forcing, for example the emission of carbon dioxide. When simulations from atmosphere-only models are used, the simulations are conditional to the observed patterns of sea surface temperature, and sometimes a particular configuration of circulation patterns, in addition to the specific external forcing. Thus, attribution of a model response to the specific external forcing is conditional on the particular sea surface temperature or circulation patterns that were used as conditioning for the simulations. As it is not possible to estimate the probability for any particular circulation configuration, it is also not possible to absolutely determine the effect of human influences. Event attribution results should therefore always be interpreted in the context of how the problem was framed, and of the conditioning used for the simulation. This makes it difficult to synthesize results from different studies and to communicate findings to non-specialists. However, conditional estimates do provide means for a story-line approach to explain attribution.

Lack of verification is an important caveat to event attribution methodologies. The counterfactual world, the world that ‘would have been’, had human influence not existed, is not observable. Thus, it is not possible to know to what extent the model has faithfully simulated that counterfactual world. More importantly, the events that are under investigation typically have a very small probability of occurrence in the factual world, and perhaps an even smaller probability of occurrence in the counterfactual world. This makes it difficult to evaluate the accuracy of the model-simulated probability, or magnitude, for the event in the counterfactual world.

DETECTION AND ATTRIBUTION OF LONG-TERM CLIMATE CHANGE

The annual mean near-surface air temperature over China has increased rapidly since the mid-20th century (Fig. 1). The rate of warming was about $0.24^{\circ}\text{C}/\text{decade}$ during 1951–2019 [2], which is greater than the global average ($\sim 0.12^{\circ}\text{C}/\text{decade}$), and the global land average ($\sim 0.18^{\circ}\text{C}/\text{decade}$) during 1951–2012 [7]. The strongest warming was observed in northern China in the winter. The rapid increase in the mean temperature was accompanied by changes in climate extremes, in moisture levels and in the wet bulb globe temperature in

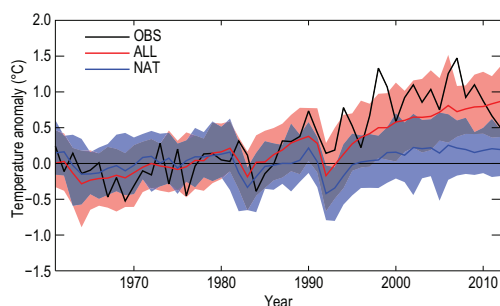


Figure 2. The observed change in mean temperature (OBS, based on Chinese 2419 station data) is consistent with the CMIP5 model-simulated change when the combined effects of all external forcings are included (ALL), but is not consistent with model simulations when only natural external forcings (NAT) are considered. The figure shows the mean temperature anomaly ($^{\circ}\text{C}$, relative to the 1961–1990 average) during 1958–2012. Shading indicates the 5–95% ranges for the simulated responses under the ALL (red) and NAT (blue) forcings, with the overlap in the range shown as dark purple. Adapted with permission from Ref. [46]. Copyright 2016 Nature Publishing Group.

summer [2,40]. A large body of literature has emerged with the aim of understanding the causes of these observed changes.

Surface air temperature

Attribution for long-term temperature changes has been based mainly on the optimal fingerprinting method [15,19], using homogenized station data from China and climate simulations from the Coupled Model Intercomparison Project, Phases 3 and 5 and more recently Phase 6 (CMIP3, CMIP5 and CMIP6 [41–43]). These studies consistently find that anthropogenic influence made an important contribution to the rapid warming.

Earlier studies have detected the effect of combined greenhouse gases and sulfate aerosols on the observed warming [44,45]. Sun *et al.* [46] expanded on the earlier studies, and were the first to consider, simultaneously, all known drivers for surface temperature change, including both external natural and anthropogenic forcings (ALL forcing) to the climate system, and the local and regional effects of urbanization. Figure 2 shows that the CMIP5 model forced with the ALL forcing reproduced the observed temperature increase in China, with a slight underestimation mostly related to urban heat island effects. Using the optimal fingerprinting method, the contributions from four drivers were quantified and separated: greenhouse gases (GHG), other anthropogenic factors (OANT) including anthropogenic aerosols and changes to land cover and land use, natural external forcings

(NAT) including solar and volcanic forcings, and urbanization (URB). Figure 3 shows that the mean temperature increased by 1.44°C (90% confidence interval: $1.22\text{--}1.66^{\circ}\text{C}$) during 1961–2013. Two-thirds of the warming, 0.93°C ($0.61\text{--}1.24^{\circ}\text{C}$), can be explained by the combined influence from the ALL forcing on the global climate system, which is similar to the observed warming in global land mean temperature during 1951–2010. GHG alone may have contributed 1.24°C ($0.75\text{--}1.76^{\circ}\text{C}$) to the warming, 35% of which may have been offset by the cooling effects of OANT (OANT is dominated by aerosols). The contribution of the cooling effect is also similar to that of global land temperatures. The NAT forcings have contributed 0.21°C ($0.10\text{--}0.31^{\circ}\text{C}$) to the warming, although the reliability of this estimate may be affected by underestimation of the volcanic forcings for the CMIP5 simulations [47]. The remaining one-third of the observed warming, 0.49°C ($0.12\text{--}0.86^{\circ}\text{C}$), was explained by urbanization effects. Two different analyses were used to estimate URB contribution and both produced similar results, indicating the robustness of the estimations. The best estimate shows a large

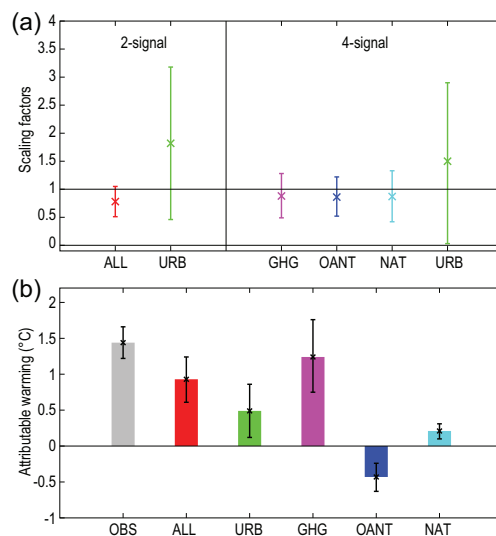


Figure 3. The signals including ALL, GHG, OANT and urbanization effects (URB) can be detected in the observed mean temperature changes in China since the late 1950s. (a) The best estimates of the scaling factors that scale the signals to match the observed temperature anomalies and their 5–95% uncertainty ranges, for the ALL and URB signal patterns in the two-signal analysis shown on the left and the URB, GHG, OANT and NAT signal patterns in the four-signal analysis shown on the right. (b) Best estimates of the observed annual mean temperature trend and its attribution to ALL and URB from the two-signal analysis, and to GHG, OANT and NAT from the four-signal analysis, along with their 5–95% uncertainty ranges. Adapted with permission from Ref. [46]. Copyright 2016 Nature Publishing Group.

contribution from urbanization, but there is a large uncertainty associated with this estimate, which is consistent with observation-based estimates [48,49]. In another study, Zhao *et al.* [50] showed that GHG-induced warming was three times that of the observed warming, offset by a large aerosol cooling of a magnitude about 1.5 times that of the observed warming. The qualitative conclusion that GHG forcing is the main contributor to the observed warming, offset by the aerosol cooling effect, is consistent with results from other studies. But the quantitative results are unlikely to be realistic and are possibly an artifact of regression degeneracy because of dependency between GHG and aerosol signals that violates the independence assumption of the regression method used in the study. Anthropogenic influences on temperature also can be detected at seasonal and/or sub-country scales. For example, they contributed more than 90% of the summer warming in eastern China during 1955–2013 [51] and are the dominant factor for the increases in annual mean temperatures in western China [52].

In addition to attribution for the mean temperature, a recent study attributed changes in an impact-relevant heat stress indicator, the wet bulb globe temperature (WBGT). WBGT takes into account both dry air temperature and humidity, and is widely used to reflect heat stress, which affects the ability of the human body to dissipate excess metabolic heat. Li *et al.* [40] examined possible human influences on the observed changes in WBGT and their contribution to China's record-high summer WBGT. They showed that the observed changes in summer mean WBGT in China since 1961 were consistent with the model-simulated response when ALL forcings were used. WBGT increased 1.17°C in western China and 0.70°C in eastern China during 1961–2010, and there was less than 1% chance that such an increase could occur without human influence. The occurrence of the highest summer WBGT during 1961–2015 has become more than 1000 times as likely in western China, and more than 140 times as likely in eastern China during 2011–2020 than it was during the 1961–1990 baseline period.

Precipitation and atmospheric moisture

Precipitation response to anthropogenic forcing is projected to be spatially variable, with a large percentage increase in high latitudes and a decrease in dry mid-latitude regions, and an increase in moist mid-latitude regions by the end of the 21st century under the RCP8.5 scenario [53]. This implies that anthropogenically induced changes in total precipitation over China could have been small so far and

would be difficult to detect because China is geographically located in the transition zones between the region with a projected increase and the region with a projected decrease in precipitation. There has not been a clear precipitation trend over China as a whole since systematic observation began in the 1960s. At a sub-country scale, observations show an increase in southern China and a decrease in northern China over recent decades [54,55]. These opposing trends are the opposite of the expected precipitation response simulated by climate models [56]. There is a range of explanations for the observed changes, including the effects of aerosols, changes in the monsoon circulation system and in sea surface temperature in the Pacific, the Indian and the Atlantic Oceans [57,58].

In a warmer world, the specific humidity of the atmosphere increases but the relative humidity over land remains unchanged, or decreases slightly [7]. Zhang *et al.* [59] found that this was the case for China: the total column moisture, or precipitable water, increased during 1973–2012 and the increase was mainly a result of anthropogenic influence. The increase in precipitable water is consistent with warming but it is unclear how the changes in moisture affect precipitation as atmospheric circulation plays an important role and the circulation response to external forcings is still largely unknown for this region.

Extreme temperature

Various indicators of temperature extremes have shown warming over China since the late 1950s [8], consistent with warming in mean temperature. In most regions, warm extremes have become more intense and more frequent, and have lasted longer; while cold extremes have become less intense and less frequent, and are more short-lived than previously. The length of the growing season has increased, and the numbers of frost days and ice days have decreased. Hot extremes, such as the number of summer days and tropical nights, have increased. There are a few exceptions, such as the cooling features seen in southwestern China [8,60]. Recent studies have consistently shown that human activities contributed to these changes.

Wen *et al.* [29] were the first to provide clear evidence of human influence on the intensity of extreme temperatures, including the annual maximum and minimum temperatures during the day and night, in China. Based on simulations by one climate model, they detected a human contribution to changes in extreme temperatures, and were able to separate the anthropogenic forcing signal from the natural forcing signal. Yin *et al.* [61] significantly

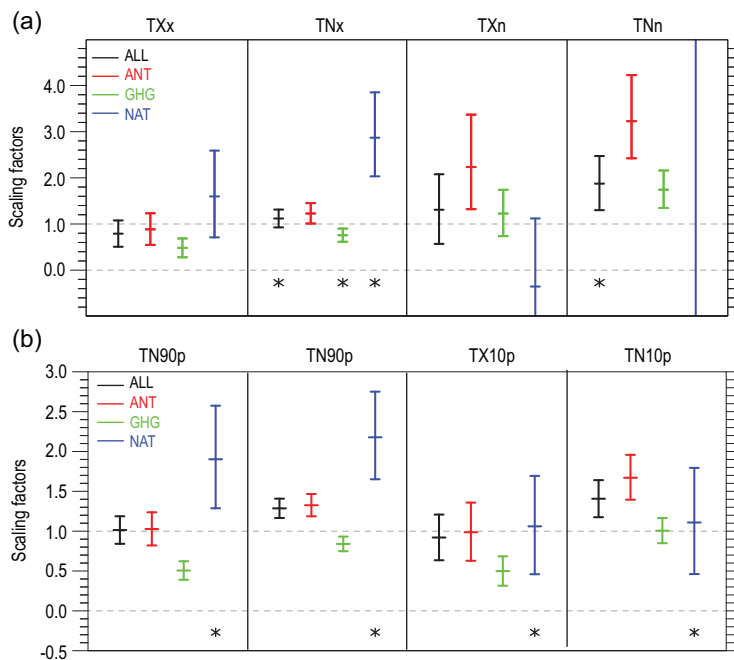


Figure 4. Human influence can be detected in the changes in the intensity (TXx, TNx, TXn and TNn) and the frequency (TX90p, TN90p, TX10p and TN10p) indices of temperature extremes. (a) The best estimates of the scaling factors and their 5–95% confidence intervals for ALL, ANT, GHG, and NAT in one-signal detection analyses for four annual series of intensity indices over China for the period 1958–2012. An asterisk indicates higher variability in the model simulations according to the residual consistency test. (b) As (a) but for the percentile frequency indices. Adapted with permission from Refs. [61] and [62]. Copyright 2017 John Wiley & Sons publications and 2016 American Geophysical Union.

improved upon Wen *et al.* [29], using a newer and more up-to-date detection and attribution technique with a multi-model ensemble of climate simulations and a longer time series of observational data. This study confirmed that the earlier findings were robust, and showed that the anthropogenic signal could be clearly and robustly detected in the intensity of extreme temperature events (Fig. 4a).

There is also clear and robust evidence of human influence on the frequency of extreme temperatures represented by the number of cold and warm days and nights (Fig. 4b, from Ref. [62]), the duration of warm and cold spells [63], or the number of frost days, tropical nights, ice days and summer days [64]. A more recent study [65] used simulations from the newest CMIP6 models and updated observations (HadEX3 data [66]), and confirmed the contribution of human influence to the frequency of temperature extremes in Asia, including China. This newer study successfully separated the influence of greenhouse gases from that of aerosols, enhancing confidence in the attribution. In addition to global warming influences, the effect of local urbanization on extreme temperature indices for eastern China was also detectable [67].

Human influence can be detected in the frequency and intensity indicators of temperature extremes at the sub-country scale. This includes detection in eastern and western China [61,62]. Additionally, Yin *et al.* [68] identified the effects of human influence in a set of 12 extreme temperature indices for the Tibetan Plateau during 1958–2017, with greenhouse gas emissions playing the dominant role. Compared with changes to temperature extremes over China as a whole, changes to temperature extremes on the Tibetan Plateau have occurred at a higher rate, which is consistent with the relatively stronger warming experienced in this region.

Extreme precipitation

A decrease in light precipitation and an increase in heavy precipitation have been detected in parts of China, especially in eastern China [69–71]. There is some consistency between these observed changes in eastern China and other regions of similar latitudes, leading to the speculation that global warming may have played a role [70]. However, there is also evidence suggesting that anthropogenic aerosols may be closely linked to such changes [70,72]. The urbanization effect on the heavy precipitation in cities has also been suggested [73]. No formal attribution study for light precipitation has been conducted so far. Thus, in what follows the focus is placed on heavy precipitation.

Observed changes in heavy precipitation in the second half of the 20th century over China are spatially non-uniform. Heavy precipitation has increased in eastern China and light precipitation has decreased [8,74]. Yin and Sun [75] studied precipitation data ending in 2017, and found increasing trends in several indices for precipitation extremes, particularly in those used to indicate heavy precipitation. Several studies have examined possible human influences on extreme precipitation, using different metrics and different methods of analysis [76–81]. Some have identified the effects of human influence on extreme precipitation, with various levels of robustness, and some have not. In general, these studies point to the emergence of the detectable effects of human influence on extreme precipitation, although the attribution is not as robust as for extreme temperature.

One set of metrics is the annual maximum precipitation amounts that fall in a single day (Rx1day), and over five consecutive days (Rx5day). These quantities are used in a wide range of applications, including engineering design, so understanding how they may change is important. At present, the most robust evidence of human influence on these

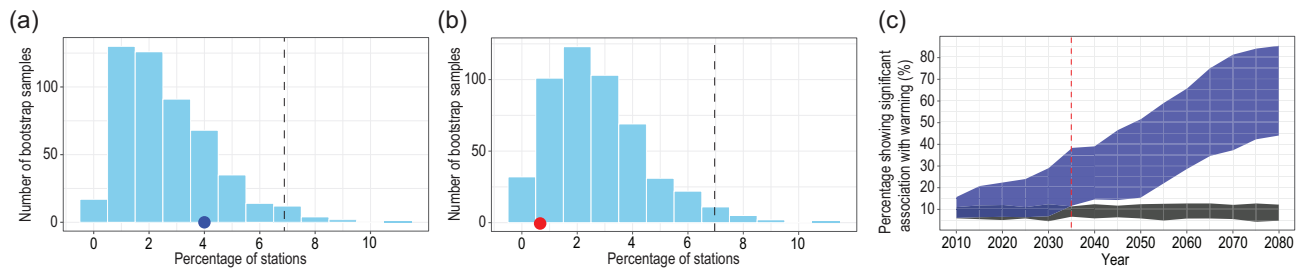


Figure 5. The observed increase in annual maximum daily precipitation is not significantly different from what could be expected by chance, but an increase can be robustly detectable by the mid-2030s. (a) and (b) Number of bootstrap samples showing the percentages of stations in China with a significant increase (a) or decrease (b) trend in extreme precipitation during the period 1961–2012 in the 500 bootstrap samples. The dashed lines mark the percentage corresponding to the 95th percentile of the probability distribution from the bootstrap samples. The solid circles on the horizontal axis show percentage of stations with significant trends in the original non-permuted station data, both are below the 95th percentile of the bootstrap samples. (c) Fraction of CMIP5 model grid boxes over China that have significant association between annual maximum daily precipitation and the global mean near-surface temperature anomalies at the 5% level. Blue shows model spread for the simulations forced with the RCP 8.5 (Representative Concentration Pathway 8.5) scenario, while gray shows expectations by chance based on 200 bootstrap samples at the 95% level. The red vertical dashed line indicates the time when an anthropogenic influence on extreme precipitation is detectable in simulations of models. Adapted with permission from Ref. [77]. Copyright 2018 American Geophysical Union.

quantities is at a hemispheric scale, for land regions where observation data are more abundant [23,25]. Li *et al.* [76] applied the method from Min *et al.* [23] and Zhang *et al.* [25] to study changes in the Rx1day and Rx5day in China, by transforming the data to probability-based indices, and then comparing the observations based on gridded precipitation datasets with CMIP5 simulations. They were able to detect an anthropogenic signal, but the signal from ALL forcings, which includes both anthropogenic and natural forcings, was surprisingly not detected. The lack of detection of an ALL forcing signal suggests that the detection of the anthropogenic signal may not be robust as a response to ALL forcing should be closer to observations than that to anthropogenic forcing alone. Li *et al.* [77] also examined changes in Rx1day in China, but used a different method. They fitted the observed Rx1day data to a generalized extreme value distribution with global mean temperature as a covariate. The detection of the global warming signal is based on a field significance test: a signal is considered to have been detected if the proportion of stations with Rx1day significantly correlated to global mean temperature is larger than would be expected by chance (Fig. 5). They found that the global warming signal was not detectable in the observed Rx1day data by the year 2012, but the signal could have been robustly detected by the 2030s in a perfect model setting based on CMIP5 simulations. While the conclusions from these two studies appear to be inconsistent, they both indicate that an anthropogenic signal is emerging in Rx1day, although detection may not be very robust at this time. This finding seems to be supported by Ma *et al.* [78], who showed that anthropogenic influence may have shifted the probability distribution for daily precipitation

towards more heavy precipitation in eastern China. This is also supported by Chen *et al.* [79], who showed that daily and hourly extreme precipitation intensified in eastern China during 1970–2017, and that the intensification can be explained by an increase in the global mean temperature.

The frequency of extreme precipitation is also used as a metric. Chen and Sun [80] defined extreme precipitation events as daily precipitation that occurs once in three or ten years during 1960–2014. They found that the nationally aggregated frequencies for these two types of extreme precipitation events increased between 1960–1979 and 1980–2014 based on 542 long-term stations in China. A similar increase was found in the CMIP5 simulations under ALL forcing but not in those under natural forcings. The similarity between the observed changes in extreme precipitation frequency and that in the ALL forcing simulations suggests a possible human influence on extreme precipitation. However, this finding in itself is insufficient for attribution of the observed changes to external forcings, as a direct causal link cannot be established. Chen and Sun [80] also used an optimal fingerprinting approach to compare nationally averaged frequencies in the observations and in the CMIP5 simulations.

The third set of metrics is the annual amount of precipitation falling during days of heavy precipitation, expressed either as an absolute amount, or as a proportion of the total annual precipitation, as defined by the Expert Team on Climate Change Detection and Indices (ETCCDI) [81]. Here, heavy precipitation days are defined as days when the daily precipitation exceeds the 99th or 95th percentiles of wet-days, from a distribution calculated for a base period. Dong *et al.* [82,83]

compared these quantities over Asia, in the observations and in the CMIP5 and CMIP6 simulations, using the optimal fingerprint method. They found an anthropogenic signal in those quantities for mid-latitude Asia. As most of the stations used in the studies are located in China, this may indicate a detectable human influence on this metric over China.

ATTRIBUTION OF EXTREME EVENTS

High temperature

Warming in China over recent decades comes with an increase in extreme high-temperature events. In particular, all five of the hottest summers in eastern China since the 1950s occurred in the 21st century [51]. The occurrence of such events, which often broke historical records, has sparked a significant effort in China to study possible human influence on their magnitude and frequency. Since the publication by Sun *et al.* [51] on the 2013 extreme hot summer in eastern China, many studies have investigated the human influence on high-temperature events in different regions of China. These studies have used different analytical methods including simulations from atmospheric-only or coupled climate models, different metrics including the number of warm spring days [84], the number of summer heatwave days [85], the maxima for daily maximum and minimum temperatures [86] and the number of consecutive high-temperature events [87]. These studies consistently show that anthropogenic forcings have substantially increased the probability of high-temperature events in China. While different factors including atmospheric circulation [88], sea surface temperature [89] and the effect of urbanization [90] have been considered, anthropogenic forcings appear to have played the dominant role in the increase in the magnitude and frequency of high-temperature events.

Coupled-model simulations have been widely used in these studies. Sun *et al.* [51] were the first to use the coupled model simulation when analyzing human influence on the 2013 summer heatwaves in eastern China. Rather than directly estimating the effects of human influence on heatwaves, which is difficult to do and is also sensitive to the definition of heatwaves, Sun *et al.* [51] analyzed human influence on 2013 summer mean temperatures. They first established that summer mean temperature and heat wave metrics are closely linked, and that summer mean temperature can be used as a proxy for summer heatwaves. Then, they used an optimal fingerprint approach to compare the observed and CMIP5-model-simulated summer mean temperatures, and

found that the observed change in summer mean temperature can be attributed to human influence. They finally reconstructed the human influence on summer mean temperature to correct bias in climate model simulations and to estimate the occurrence probabilities for 2013-summer-like temperatures in a model world, both with and without human influence. Because variability in model simulations is validated with observations, and because the model bias is corrected, the probability ratio should be quite reliable when calculated this way. This approach was later adopted in several other studies, including Song *et al.* [84] who looked at the warm spring in northern China in 2014, Sun *et al.* [86] who studied high temperatures in western China in 2015 and Li *et al.* [40] who examined the effects of human influence on hottest WBGT. Miao *et al.* [91] applied a similar but different method to study human contribution to the record-breaking temperature in northwest China in July 2015, involving coupled model simulations, and found that human influence had increased the probability of the event three-fold. Zhou *et al.* [90] considered the effects of warming-induced thermodynamic and dynamic changes, as well as urbanization, and found that they all contributed to the 2018 record-breaking summer heat in northeastern China.

Several studies have relied on atmosphere model simulations to estimate the effects of human influence on extreme heat. Typically, these models have been driven by observed sea surface temperature (SST) and sea ice to simulate the world as it has been, and by SST and sea ice conditions with the effect of global warming removed to simulate the world as it would have been without human influence. Some studies use large-ensemble simulations conducted with the HadGEM3-A model because of the availability of the simulations and their near real-time updates [92]. For example, Chen *et al.* [85] analyzed July 2017-like heat waves over central-eastern China. They found the event to be a one-in-five year event, but this would have been rare in a world without human influence.

While simulations from both coupled and atmosphere-only models have been used for event attribution, and results can be quite similar, it is important to stress again the differences between the two for results to be interpreted appropriately. Simulations from atmosphere-only models are conditional on the observed spatial-temporal patterns of sea surface temperature and sea ice, and thus the occurrence probabilities are conditional on the historical state of atmosphere-ocean variability. As it is not possible to estimate the probability of the particular path that atmosphere-ocean variability has experienced, it is also not possible to estimate

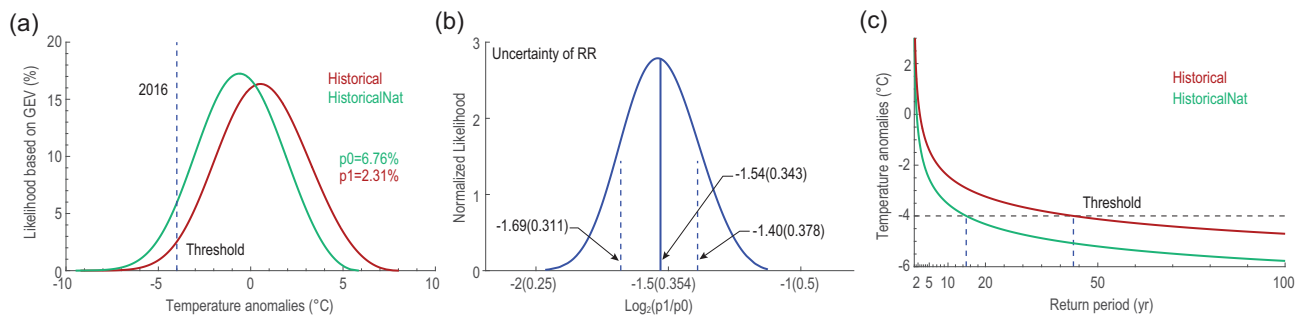


Figure 6. Warming has resulted in a decrease in the occurrence probability of a 2016-like cold surge. (a) The GEV distributions fitted to anomalies of pentad mean daily minimum temperature (Tmin) (°C) during midwinter 2016 averaged over eastern China of historical simulations forced with anthropogenic and natural forcings and historicalNat simulations forced with natural forcings. A shift in the probability distribution because of warming is clearly seen. The dashed line indicates regional average pentad Tmin anomaly for 21–25 Jan 2016 in the observations. (b) Uncertainty in the attributable risk ratio with dashed lines marking one standard deviation. (c) Return period (years) for an extreme cold event with an intensity equal to, or greater than the Jan 2016 event in historical, and in historicalNAT simulations. The black dashed line shows the anomaly of the event and the dashed blue lines represent the return periods of the event in the world with (the line to the right) and without (the line to the left) human influence. Adapted with permission from Ref. [95]. Copyright 2018 American Meteorological Society.

the relevant unconditional probabilities, and thus not possible to determine the corresponding probability ratio. Coupled-model simulations are driven by external forcings only, and are not constrained by observed SST and sea ice. As such, there can be a large bias in both the mean and the variability for a particular region. Such a bias needs to be carefully considered. The bias can be adjusted if an optimal fingerprint approach is used, such as in Sun *et al.* [51]. Confidence in probability estimates is high if observed long-term changes can be attributed to human influence. There may be a large difference in event attribution statement based on these two approaches. For example, Sun *et al.* [93] demonstrated that the use of AMIP-type and CMIP-type simulations can lead to large differences in probability estimates.

Cold event

Warming has resulted in a reduction in extreme cold events in China. Fewer events also mean less attention directed at them, but the 21–25 January 2016 cold event caused widespread impacts including snowfall in Guangzhou and provided an opportunity to closely investigate the human influence on cold events. Three papers have studied this event so far. Two concluded that human influence had made such events less likely to occur [94,95], but the other study suggested that probabilities of extreme circulation anomalies underlying the extreme cold surge have increased because of human-induced Arctic warming [96].

Sun *et al.* [94] analyzed the event using an approach similar to that of Sun *et al.* [51], finding that winter mean temperature had increased as a result of

human influence and that the occurrence probability for the 2015/2016 winter-like extreme temperature decreased by about 89% for northern China, and by about 69% for southern China. Qian *et al.* [95] took a quite different approach by estimating occurrence probability for similar events in a world with or without human influence. They fitted generalized extreme value (GEV) distributions to pentad mean daily temperature anomalies for the dates of the event in the simulations conducted with an atmospheric model (HadGEM3-A) that were forced with or without human influence. It is clear from their analysis that the probability distributions of such events shifted to the left in the world with human influence, indicating a reduction in the occurrence of probability for such events (Fig. 6). They concluded that human influence may have reduced the occurrence probability for the 2016 cold event by about two-thirds. Ma and Zhu [96] compared the circulation regime underlying the cold event in the simulations conducted with the MIROC5 model that mimicked the factual world and a counterfactual world. They showed that the occurrence probabilities of circulation anomalies underlying the cold event have increased in response to anthropogenic forcings. They further speculated that the January 2016 cold surge could be a result of global warming. However, it is difficult to validate such speculation because changes in circulation do not necessarily translate into a similar change in the occurrence probability of the cold event. For example, while internally generated circulation anomalies alone could have produced the 2010 Russian heatwave of the magnitude as observed, there was a large 80% probability for the heatwave to not have occurred without human influence [97].

Heavy precipitation

Event attribution studies of heavy precipitation have used different metrics including amount, frequency, intensity and duration. As different studies have focused on events that occurred in different regions and at different times, and have produced wide-ranging results from strongly attributing heavy precipitation events to human influence to natural variability, it has been difficult to synthesize results from these studies.

Several studies have used simulations by coupled models [98–100]. Sun *et al.* [100] focused on the heaviest June precipitation in South China, and showed that anthropogenic influence had doubled the probability of 2017-like heavy precipitation in southeastern China. Sun and Miao [98] and Yuan *et al.* [99] found large contributions from El Niño and from anthropogenic influences to the extreme precipitation events they studied. Burke *et al.* [101] used HadGEM3-A simulations to investigate the effects of human influence on the duration, amount and intensity of consecutive wet events in May 2015 in 12 sub-regions of southeast China. They found an anthropogenic signal in three out of the 12 regions and concluded that anthropogenically induced climate change has increased the probability of short-duration, intense rainfall events in parts of southeast China. However, Li *et al.* [102] concluded that the strong El Niño in 2015 may have increased the occurrence probability for the rainfall events rather than these being driven by anthropogenic forcing, despite analyzing the same set of model simulations. Zhang *et al.* [103] used simulations conducted with the same model and showed that anthropogenic influence increased the occurrence probability for highest daily precipitation but not for persistent heavy rainfall for the 2018 heavy-precipitation event in central-western China. Based on a set of CMIP5 model simulations including those of HadGEM3, the July 2016 heavy precipitation event over Wuhan was attributed to human-induced warming and El Niño [104].

Heavy snowfall as an important form of heavy precipitation has shown an increase in parts of northern China in the recent decade [105]. These changes seem to be linked to changes in atmospheric circulation [106], but the causes of the circulation change are unclear.

Drought

A drought is an event of prolonged conditions with a well below-average water supply that results in negative impacts on the natural systems and economic sectors. Because of the complexity of impacts, droughts are often not directly mea-

surable, but can be characterized using different indicators. Different drought indices such as the Standardized Precipitation Index, Standardized Precipitation-Evapotranspiration Index and the Palmer Drought Severity Index, have been used to study past changes in droughts for different parts of China, making it difficult to intercompare and synthesize results across the studies. Attribution studies are limited to attributing specific drought events, finding an increase in the probability of the drought events as a result of human influence, including the autumn drought of 2009 in south-western China [107] and the late spring drought of 2018 in South China [108]. Li *et al.* [109] found detectable human contribution to the intensification of summer hot drought events in northeastern China where drought events were loosely defined as high temperature and low precipitation through a joint probability distribution of precipitation and temperature. As drought events are defined based on the joint probability distribution, it is difficult to compare those events with droughts that are defined based on traditional drought indicators. Overall, while there is increased attention in attributing droughts, there is still a lack of general understanding of the human influence on droughts in China.

CONCLUSION AND FUTURE DEVELOPMENT

Despite entering the fields of climate change detection and attribution and event attribution relatively late, Chinese researchers have made significant progress over recent years. These studies have established clear and robust evidence of the effects of human influence on mean and extreme temperatures, and emerging evidence for the effects of human influence on extreme precipitation (Box 1). However, a significant gap remains in our understanding of how human influence affects other aspects of climate change and climate impacts in China.

Human influence on the temperature in China has now been studied extensively. The impact of human activities on temperature is clear, regardless of differences in the metrics including long-term changes in mean or extreme temperatures, and the frequency and magnitude of events of temperature extremes. The effects are also clear, irrespective of differences in the methods used for the analyses. Anthropogenic forcings, dominated by GHG emissions, are the main driver for the increases in mean and extreme temperatures that have occurred since the 1960s. The cooling effects from other

Box 1. Summary of attribution of human influence on changes in China’s climate since the mid-20th century.

Changes in long-term mean	
Climate variables or phenomenon	Attribution of human influence
Mean temperature	Very likely the main driver for the observed increase
Total precipitation	Lack of change in observations
Frequency and intensity of hot extremes	Very likely the main driver for the observed increase
Frequency and intensity of cold extremes	Very likely the main driver for the observed decrease
Frequency and intensity of heavy precipitation	Human influence for an increase in heavy precipitation emerging
Drought	Limited evidence for increase in droughts
Extreme events	
Type of events	Attribution of human influence
Extreme heat	Very likely increase in occurrence probability
Extreme cold	Very likely decrease in occurrence probability
Heavy precipitation	Mixed signal (increase in probability for some events but decrease for other events)

anthropogenic forcings including aerosols partially offset the GHG-induced warming. But precisely separating the cooling effect of aerosol from the GHG’s warming effect on China’s temperature is difficult because these effects are highly colinear. Urbanization also significantly contributed to warming, especially at a local level. Together, these have led to an increase in hot extremes and a decrease in cold extremes: hot extremes have become more frequent, more intense and longer in duration, while cold extremes have become less frequent and less intense. For example, the 2013 summer heatwave in eastern China would have been extremely unlikely without the effects of human influence, and it has now become a one-in-four to one-in-five year event. This has clear implications for future changes in extreme high-temperature events. The observation-based future projection shows that the 2013-like heatwave will become a once-a-year event around the 2050s, even under a medium emission scenario (Fig. 7). This conclusion is confirmed by another independent study, which used large-ensemble runs and a model-bias adjustment method [110].

There is not clear evidence of anthropogenic influence on total precipitation, although some numerical experiments have shown the effects of aerosols. The evidence of human influence on extreme precipitation is emerging, however. This includes detection of an anthropogenic signal in long-term changes to the magnitude and frequency of heavy precipitation, although the detection is not very robust because of variations in the methods used for data processing and analysis. These findings also project an increased magnitude or frequency for some extreme precipitation events. The effects of human influence on individual heavy precipitation events are still uncertain. Conclusions vary from study to study, which suggests that the effect of hu-

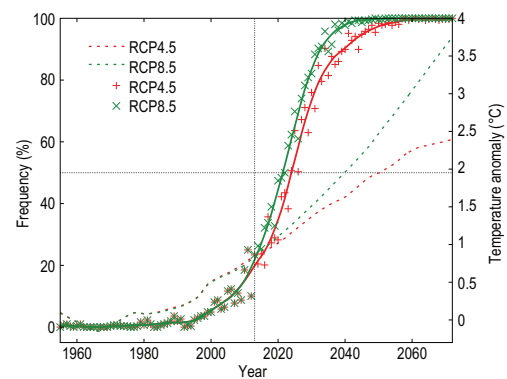


Figure 7. Frequency of 2013-like summer increases rapidly. The figure shows time evolution (solid lines) of the frequency for summer temperature anomalies (relative to the 1955–1984 mean) that are above 1.1°C in observation constrained projection under RCP4.5 and RCP8.5 scenarios (left-hand scale). The solid smooth curves show LOESS (local regression) fitting. For reference, the dashed curves show the projected changes in mean temperature (right-hand scale) under RCP4.5 and RCP8.5 scenarios. Adapted with permission from Ref. [51]. Copyright 2014 Nature Publishing Group.

man activities may either increase or decrease the occurrence of heavy precipitation in different regions or scenarios.

Human influence on other climate variables or climate extremes has not been widely studied, such as wind, extreme wind, typhoon and climate impact relevant variables. Among these variables and events, change in mean wind speed has been fairly extensively detected [59,111–113], and the wind variability and change have started to be attributed to factors such as increased surface roughness [114] and anthropogenic warming [115]. The changes in circulation, such as the weakening and widening of the Hadley circulation [116], would also have important

influence on regional climate change in China. End-to-end event attribution [37], which attributes the impacts from climate events to human influence, is still lacking. There is also a need to understand, and to reduce the uncertainty for attribution, and event attribution in particular. Significant work is required to meet climate adaptation and mitigation policy-making needs. Identification of the effects of climate change mitigations will be another significant challenge.

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